MODELING AND FORECASTING MACROECONOMIC FUNDAMENTALS IN NIGERIA

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ABSTRACT

This paper predicts the behaviour of selected macroeconomic variables in Nigeria using VECM to analyse quarterly data for the period 1999Q1–2016Q4. The findings show that the static solution forecast of the estimated model outperforms the dynamic version. Specifically, the model predicted the behaviour of the variables quite well amidst notable breaks that mimicked the actuals. The ARIMA model validated this finding because the model that accounted for breaks performed better than without breaks. The models also forecasted the growth trajectory of the economy in the build-up to the 2016 recession as well as the bearish sentiments in the stock market and depreciation of the naira. In addition, while the VECM performs better than the ARIMA model, structural breaks are important and should be considered when forecasting macroeconomic series. The study suggests that monetary and exchange-rate policy consistency is crucial for smoothening macroeconomic fluctuations and promoting market stability.

Keywords: All-Share Index, GDP, Business Cycle, Forecasts, Vector Autoregression, ARIMA, Nigeria

JEL Classification: C32, E32, E37

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1. INTRODUCTION

The analysis of business cycles is important due to concerns about economic slowdowns and macroeconomic stability. A business cycle reflects fluctuations in economic activity characterised by expansion and contraction states (Ng and Wright, 2013, p.1123). A recession is a phase that exhibits a slowdown in output for at least two consecutive quarters (CBN, 2012). Recessionary periods are characterised by weak macroeconomic fundamentals. These issues are of primary concern to government's macroeconomic policy. The 2016 recession witnessed in Nigeria may be traced to fiscal constraints due to oil revenue shortfalls, energy deficit, low investor confidence and policy uncertainty. Although several policy responses were deployed by government, post-recessionary recovery is quite slow despite the GDP rebound of 0.55% reported by the Nigerian Bureau of Statistics(NBS) in Q2 2017. Therefore, reliable forecasts can serve as valuable inputs for planning.

The Nigerian economy recorded a contraction of 0.36%, 2.06% and 2.35% in the first, second and third quarters of 2016 respectively. This may be traced to the decline in international crude oil price from an average of about $110 in 2014 to an abysmal $30 as at January 2016. This was worsened by low oil exports due to disruption of production from about 2.1 million to around 1 million barrels per day. Consequently, external reserves declined substantially from about $60 billion in 2007 to about $24 billion as at September 27, 2016. The vulnerability of the economy to oil-price shocks as well as inadequate fiscal buffers intensified the recessionary pressure. The parallel exchange rate depreciated from ₦197 to ₦309 per US dollar and to a staggering ₦430 (September 2016) following the adoption of the flexible exchange rate in June 2016.

There is an extensive literature that examines macroeconomic performance (see Olofin *et al.*, 2009 for Nigeria; Ng and Wright, 2013 for a global perspective; Banerjee *et al.*, 2005 for the EU; Hong & Tan, 2014 for a comparison of forecast performance by international institutions; and Diebold, 1997 for a historical comparison of business cycle episodes). The literature for Nigeria witnessed a proliferation of macroeconometric models for forecasting and policy simulations such as NISER (2015), CBN (2010) and Olofin et al. (2009). In addition to endogeneity bias, these models were unable to predict downturns, despite the fact that the variables track the actuals well. This paper overcomes this limitation using a restricted Vector Autoregression (VAR)-based forecast model. A major advantage of this procedure over macroeconometric models is its treatment of identification problem that arises regarding endogeneity and exogeneity of variables.

Other existing studies such as the CBN (2015) focus on forecasting real GDP using a dynamic factor model within a state-space framework. In this model, shocks are common across sectors while others are idiosyncratic (Diebold, 1997, p. 11). Forecasts using Vector Error Correction Model(VECM) are in most cases better than those obtained from system of equations (Asteriou &Hall, 2007). This modelis preferred because the evolution of macroeconomic variables is characterised by interdependent processes and lag effects are important for predictions (Pecican, 2010). Although Structural Vector

Autoregressive (SVAR) models have been used to analyse macroeconomic relationships in Nigeria (Akpan & Atan, 2015; Ekong & Effiong, 2015), the assumption that shocks are orthogonal is restrictive (Gottschalk, 2001). This implies that forecasts using this approach may lead to misleading inferences due to prior restrictions on parameters of the model.

This paper forecasts macroeconomic fundamentals using univariate and multivariate approaches. The latter is a VECM used to generate forecasts while the former is based on rolling and expanding window Autoregressive Integrated Moving Average (ARIMA) forecasting techniques. These models have been shown to perform well in tracking the behaviour of macroeconomic variables (Doguwa & Alade, 2013; Okafor & Shaibu, 2013). The structure of this paper is as follows. Section tworeviews the literaturewhilesectionthree presents the methodology. After a presentation of results in section four, the paper offers some conclusions and recommendations in section five.

2. LITERATURE REVIEW

The theoretical underpinning of recessions can be traced to the Keynesian perspective where effective demand plays a vital role in output determination. This underscores the role of fiscal policy tools as a panacea for growth. The neoclassical view gave rise to models that analyse the macro economy from a monetary perspective through the dynamics of investment and interest rate. However, these models did not account for expectations, which are important because agents form expectations based on available information. This underscores the need to incorporate dynamics in forecasting macroeconomic series.

Recent theoretical developments of RBC models (Rebelo, 2005; Plotnikov, 2017; and Gomme *et al.,* 2017) opine that fluctuations are outcomes of shocks under perfect competition. It assumes that output is subject to contemporaneous distortions from steady state. The shocks are driven by changes in technology rather than monetary conditions and expectations. These shocks are propagated through changes in the structure of production (Plotnikov, 2017; Gomme *et al.*, 2017). Another extension is the two-sector RBC model of Whelan (2003) and Ireland & Schuh (2008) that distinguishes between consumption and investment goods with constant shares along the balanced growth path. The shares exhibit trends driven by technological progress.

Webb (1994) compares forecasts and establishes the potency of VAR over macro-econometric models. Bhattacharya *et al.* (2004) predict the growth rate of GDP using a model that accounts for breaks in selected Indian states. They find that the model tracks the variables but note the declining share of agriculture and manufacturing in GDP relative to services. Creal *et al*. (2010) observe that unemployment and inflation inhibit the cycle, while productivity, manufacturing, and real consumption of nondurables plus services lead the cycle. Berge (2014) applied four model selection methods in order to predict business cycle turning points in the US and found that models produced by Bayesian model outperformed equally-weighted forecasts, even for the out-of-sample forecasts.

Banerjee *et al.* (2005) forecast selected macroeconomic variables using dynamic factor models for five EU member countries. They find that factor models work well in general albeit differences observed across countries. Lack (2006) assesses Swiss predictions of inflation between 1987 and 2005 and finds that combining different VAR forecasts improves the quality of predictions. Fossati (2015) relies on a panel of macroeconomic indicators to predict recessions using Probit models in the US. The findings suggest that models relying on financial and real activity indicators maintain their fit throughout the sample and exhibit better forecast performance.

CBN (2010) uses a macroeconomic model for Nigeria to examine the effectiveness of macroeconomic policy and found that the in-sample performance was good in terms of its tracking power. Doguwa &Alade (2013) examine four inflation forecasting models using seasonal and structural ARIMA processes and compare the performance using the pseudo-out-of-sample forecasting procedure between July 2011 and September 2013. The findings reveal that the best forecast performance is demonstrated by the all-items composite index model. The authors note that the eight-period ahead forecast performs poorly whereas the ten-month ahead food price forecasts using the seasonal ARIMA performed better. CBN (2015) predict RGDP in Nigeria using a dynamic factor model covering the period Q2 2014- Q4 2015. They find that the growth rate of RGDP hovered above 6.5% during the review period. From an actual growth rate of 6.54% in Q2 2014, output growth was forecasted to rise to 6.93% in Q3 2014. The model also forecasted a marginal slow down towards the end of 2014 and 2015.

Chin (2013) examines the role of macroeconomic fundamentals in Malaysian post-recession growth using cointegration and VECM. The results of the long-run cointegrating relationship reveal that an increase in exports and government expenditure, as well as exchange rate depreciation, promote long-term growth. The study also showed that an increase in the rate of inflation, interest rate, and imports dampen growth. Liu & Moench (2014) reassess the predictability of US recessions from three months to two years ahead for a large number of leading-indicator variables using probit model. The study reveals that while treasury term spread has the highest predictive power, adding lagged observations of the spread significantly improves predictability.

Hong &Tan (2014) evaluate forecast performance of the UN, IMF and World Bank models. The forecasting performance of the UN's model was preferred to those of the other two organizations for the period 2000-2012 based on traditional statistical loss functions. However, the forecasts of these organisations missed the 2009 recession by a large margin. Okafor &Shaibu (2013) rely on ARIMA to analyse inflation in Nigeria and test the forecast performance of the model for the period 1981-2010. Utilising RMSE, they find that ARIMA(2,2,3) is the most appropriate model for forecasting inflation. Alege (2010) examines the role of Nigeria's macroeconomic policies in managing the pro-cyclical impact from exogenous shocks utilising a VAR model for the period 1970Q1–2006Q4. The findings suggest that the economy is far from converging towards a sustainable equilibrium in the short run but the forecasts indicate that the variables appear to converge to steady state.

3. DATA AND METHODOLOGY

3.1 The Model and Estimation Technique

The empirical analysis proceeds with the assumption that cycles are driven by internal and external perturbations based on the IS-LM-BP framework. This is applicable to the case of Nigeria in view of the country's integration with the rest of the world. Thus, a multivariate VAR model that accounts for real gross domestic product, all-share index, money supply, domestic price, exchange rate and trade balance (See Table 1 for a detailed description of the data) is specified:

$$\boldsymbol{Y_t} = A + B_1\boldsymbol{Y_{t-1}} + \cdots + B_p\boldsymbol{Y_{t-p}} + \boldsymbol{U_t}, \quad (1)$$

where $\boldsymbol{Y_t}$ and $\boldsymbol{Y_{t-1}}$are *mx1* multi-dimensional vector of variables. Notice the *mx1* error vector *Ut* measures the extent to which $\boldsymbol{Y_t}$cannot be determined exactly as the linear combination of the lagged values of$\boldsymbol{Y_t}$with parameters *A* andB_i(*i*=*1,…,p*).

The VAR model developed by Sims (1980) arose from the limitations identified in macroeconomic models. The existence of simultaneity bias implies that variables (endogenous and exogenous) should be treated the same way. However, the data used are *I(1)* and having established the existence of a long-run equilibrium relationship between the variables, the use of VECM is imperative. This approach entails summarising the contemporaneous correlation between the observed series and using the output to generate forecasts. The model is specified as follows:

$$\Delta\boldsymbol{Y_t} = \theta_1\Delta\boldsymbol{Y_{t-1}} + \cdots + \theta_p\Delta\boldsymbol{Y_{t-p}} + \alpha\boldsymbol{ECT}_{t-1} + \varphi_t\boldsymbol{D} + \boldsymbol{\mu}_t, \quad (2)$$

where ***ECT*** is the error correction term and ***D***, a dummy variable used to account for potential breaks. Further checks are conducted using the Box-Jenkins approach. In this case, trends driven by the cumulative effects of random disturbances are relied upon to formulate, estimate, and diagnose the model (Asteriou & Hall, 2007). The underlying notion behind the approach is parsimony as parsimonious models yield better forecasts than over-parameterised ones. At the heart of this methodological pursuit is the use of Autoregressive Integrated Moving Average (ARIMA-p,d,q) model specified as follows:

$$Y_t(1 - \gamma_1 L - \gamma_2 L^2 - \cdots - \gamma_p L^p) = (1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_p L^p) \quad (3)$$

Equation (3) shows that an integrated series must be differenced *d*times before it can be represented by a stationary and invertible ARMA process. If this ARMA representation is of order (p,q) then the series follows an ARIMA(p,d,q) representation. Diebold (1997) observes that much of macroeconomics is concerned with multivariate relationships whereas the Box-Jenkins approach is based on a univariate structure. Nevertheless, the forecasting ability of these models may be compared.

The post-estimation diagnostics of the forecast errors is carried out using the following statistical loss functions: (i) Root Mean Square Error ($RMSE = \sqrt{\sum_{t=1}^{T} \varepsilon_t^2 / T}$), (ii) Mean

Absolute Errors ($MAE = \sum_{t=1}^{T} |\varepsilon_t|/T$), and (iii) Mean Absolute Percentage Error ($MAPE = \sum_{t=1}^{T} |f_t - g_t|/g_t$, Where f_t is the forecast and g_t is the actual growth rate at time t.).

2.2. Types and Sources of Data

Quarterly data (1999Q1-2016Q4) is used and they are sourced from the CBN Statistical Bulletins. Table 1 describes the data.

Table 1: Data Description

Variable	**Description**
All-share Index (ASI)	This is the capitalization weighted average share prices of all companies listed on the Nigerian Stock Exchange.
Exchange Rate (EXR)	This is the price a country's currency can be exchanged for another currency of the world. Naira-USD rate
Inflation (INF)	Inflation is the consumer price index that reflects the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services.
Money Supply (MSS)	This is measured as the total monetary liabilities of the CBN (M2)
Real Gross Domestic Product (RGDP)	The total value of goods and services produced in an economy deflated by domestic prices.
Trade Balance (TRA)	The ratio of exports to imports.

All variables described in Table 1 were then expressed in logarithmic form prior to estimation.

4. RESULTS AND ANALYSIS

4.1 Basic Results

Descriptive statistics show that the series record high standard deviations. The difference in averages makes a case for taking the natural logarithms of the data. In terms of symmetry, the series exhibit a moderate positive skewexcept for exchange rate that has a long right tail. The positive kurtosis for all the series indicates a steep distribution, with that of exchange rate being relatively flatter. For all the series excluding net export, the null hypothesis of normality is rejected based on the Jarque-Bera statistic. The correlation analysis shows that net export is negatively correlated to real GDP while other variables are positively correlated, with the exchange rate, inflation and money supply recording correlation coefficients above 50%. (See Appendices 1 and 2). The residual diagnostic check (not presented due to space) suggests that the shocks are white noise albeit notable breaks are observed in the series that coincide with the 2016 slowdown.

Table 2 shows the residual covariance matrix and the off-diagonal elements are non-zero, indicating that the residuals are not significantly correlated. The residual autocorrelation Lagrange multiplier test suggests a rejection of the null hypothesis of no autocorrelation at the 5th lag. This validates our selection of 4 as the optimal lag length. The VAR literature does not suggest taking differences of series even if they are non-stationary at levels (Sims, 1980). Nevertheless, preliminary checks for unit root and long-run relationship were performed and the results are presented in Appendices 3 and 4 respectively. All the variables are stationary at first difference and there exists a long-run association between the variables considered. This motivates our use of VECM as the appropriate model to forecast the series.

Table 2: Covariance Matrix of Residuals

	LASI	LEXR	LINF	LMSS	LRGDP	LTRA
LASI	0.020541	-0.003339	0.000203	0.000637	0.017673	0.001790
LEXR	-0.003339	0.003578	0.000258	0.000184	-0.005042	-0.002667
LINF	0.000203	0.000258	0.000683	0.000268	-0.001902	0.000567
LMSS	0.000637	0.000184	0.000268	0.003750	-0.002302	0.002803
LRGDP	0.017673	-0.005042	-0.001902	-0.002302	0.691352	0.015136
LTRA	0.001790	-0.002667	0.000567	0.002803	0.015136	0.031861

All variables described above were expressed in their logarithmic forms prior to estimation. The prediction using the VECM is conducted using stochastic simulation with static solution dynamics. This is because the relationships modelled may not hold over the forecast period due to random disturbances. In addition, the coefficients are estimated and not predetermined values. Figure 1 shows that the forecasts closely mimic the actual variables, falling within the validation bounds. Although the dynamic solution was considered, the static solution of the model was selected because it performed better. Moreso, this approach uses the actual value of the lagged series to perform the forecast.

From Figure 1, there is no evidence of the series deteriorating over time; rather, the predicted series track the actual variables, confirming the earlier works of CBN (2010) and NISER (2015) on Nigeria. The behaviour of stock prices remained volatile; exhibiting a downward trend due to contemporaneous capital reversal as well as upward pressure on the naira exchange rate. This contributed to the increase in domestic prices which mirrored the monetary policy stance as indicated by the movement of broad money supply. This is in agreement with the findings of Doguwa &Alade (2013). Although modest developments in the RGDP are visible, a glaring feature is the rebasing exercise that instantaneously changed Nigeria's growth trajectory. The decline in the volume of trade may be traced to several binding constraints such as restrictions on foreign exchange as well as low oil exports due to contractions in domestic production. This is apparent when observed from the first quarter of 2013 during which increased insecurity in the oil-producing region led to a negative effect on oil output. This trend reversed during the first quarter of 2016 when trade flows in the oil and gas sector began to improve.

The evaluation outcomes of the dynamic and static VECM models are reported in Table 3. Information on the RMSE, MAE, MAPE and Theil's indices are provided to assess the models' forecast performance. The result shows that the static model outperforms the dynamic version. This may be explained by the fact that the dynamic version uses the actual values of endogenous variables to solve forward for the forecast period, hence the deterioration of forecast performance of the variables over the prediction horizon. Interestingly, the MAPE generally revealed a poor forecast performance for all the variables given the relatively high values of the computed statistic. Nevertheless, the indices are quite plausible and suggest that the model is able to track the actual values of the endogenous variables. An important implication of this finding is the treatment of all variables as endogenous and this departs from previous models proffered by Olofin *et al.* (2009).

4.2 Further checks: Univariate ARIMA Model Results

To check for robustness, the ARIMA-based expanding and rolling window forecast strategies are used. In the former approach, the estimation window expands as we forecast into the future. Its major advantage over the rolling window strategy is that predictions are made over the same forecast period. This is particularly important when computing the RMSE because it requires only h-step ahead forecasts. Under the rolling window approach, the estimation sample is fixed such that the size is less than the total observations and it rolls forward as the forecastis generated over the same horizon.

For the LRGDP series, the 2010 rebasing exercise which resulted in notable breaks in the series around the 2010Q1 is captured in order to arbitrage between the results with and without structural breaks. The results indicate that the expanding window strategy yields better forecasts compared with the rolling window approach as indicated by the various forecast evaluation statistics and minimum bias recorded (See Tables 4 and 5). The analysis suggests that forecasting real GDP yields better outcomes when structural breaks are considered.

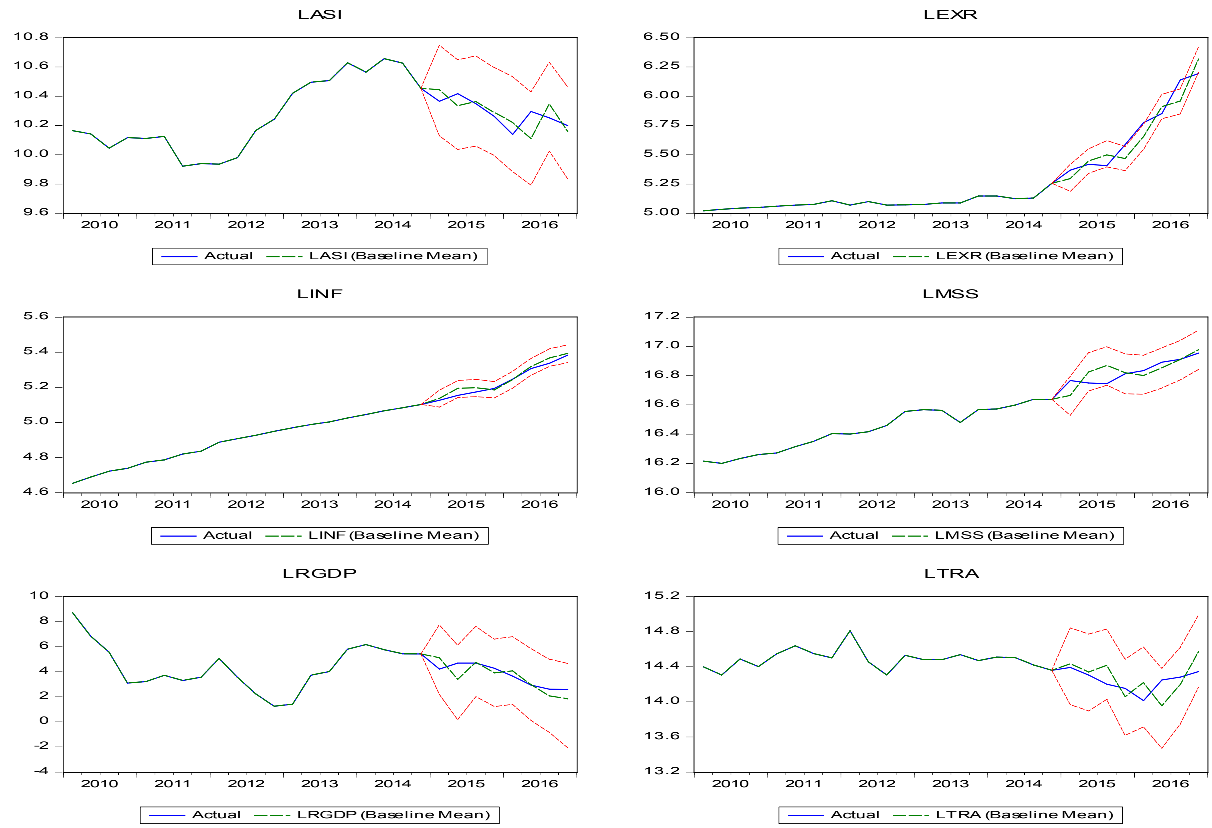


Figure 1: VECM-based forecasts

The forecast performance of the LASI using the rolling and expanding window forecast approaches with and without structural breaks is presented in Tables 6 and 7. The analysis shows that the evaluation statistics worsen over the forecast horizon, meaning that the forecasts become more uncertain in terms of the RMSE, SE, MAE and MAPE. This implies that accounting for breaks is important for forecasting stock returns in Nigeria. Overall, the expanding window forecasts of LASI performs better than the rolling window predictions in view of the relatively lower values of the forecast error.

Table 3: VECM Forecast Evaluation

Variable	RMSE		MAE		MAPE		Theil	
	Dynamic	Static	Dynamic	Static	Dynamic	Static	Dynamic	Static
LASI	5.521	5.519	5.680	5.516	99.723	99.711	0.974	0.973
LEXR	5.267	5.256	5.264	5.253	100.164	100.160	0.976	0.976
LINF	16.740	16.726	16.740	16.726	99.980	99.979	0.999	0.999
LMSS	3. 678	3.555	3.389	3.359	99.990	99.838	0.977	0.976
LRGDP	10.338	10.314	10.307	10.282	99.998	99.988	0.932	0.932

LTRA	14.237	14.230	14.236	14.227	99.891	99.886	0.988	0.988

Table 4: E Expanding Window Forecast Approach (LRGDP)

	Horizon 1		Horizon 2		Horizon 3		Horizon 4	
	break	no break	break	no break	break	no break	break	no break
Bias	-0.25	-0.817	-0.5	-1.487	-0.705	-2.022	-1.025	-2.612
MSE	1.557	3.142	3.521	7.808	5.663	12.363	8.051	16.208
RMSE	1.248	1.773	1.877	2.794	2.38	3.516	2.837	4.026
SE	1.222	1.573	1.809	2.366	2.273	2.876	2.646	3.063
MAE	1.064	1.462	1.585	2.332	1.955	2.916	2.287	3.382
MAPE	0.295	0.392	0.471	0.736	0.582	0.978	0.678	1.136

Table 5: Rolling Window Forecast Approach (LRGDP)

	Horizon 1		Horizon 2		Horizon 3		Horizon 4	
	break	no break	break	no break	break	no break	break	no break
Bias	-0.176	-0.235	-0.39	-0.407	-0.574	-0.516	-0.883	-0.734
MSE	1.683	2.639	4.082	6.917	6.529	11.073	9.032	15.043
RMSE	1.297	1.625	2.02	2.63	2.555	3.328	3.005	3.879
SE	1.285	1.607	1.983	2.598	2.49	3.287	2.872	3.809
MAE	1.079	1.319	1.696	2.132	2.106	2.791	2.426	3.209
MAPE	0.284	0.326	0.488	0.589	0.613	0.823	0.698	0.904

Figure 2 shows the plots of fan charts of the various series from 2014Q1 with the initial trend prior to the selected date. This is used to check the potency of forecasts.

Table 6: Expanding Window Forecast Approach (LASI)

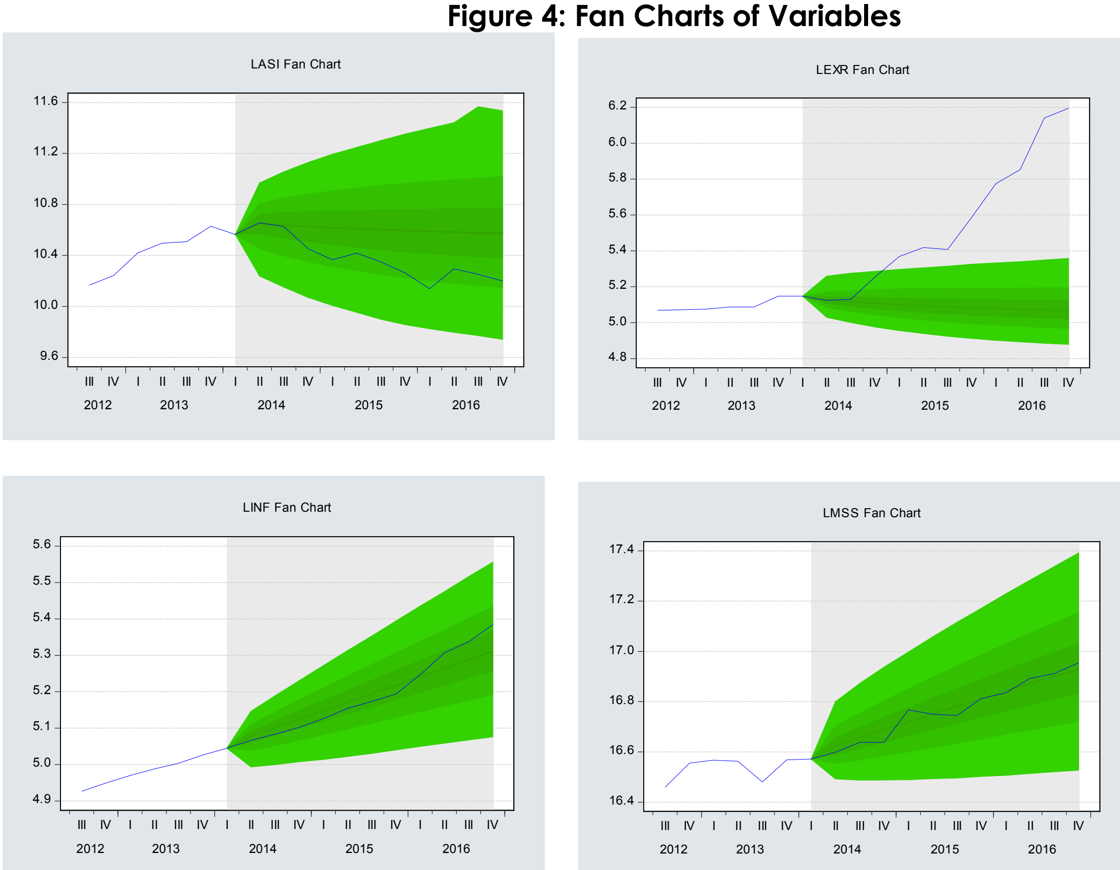
	Horizon 1		Horizon 2		Horizon 3		Horizon 4	
	break	no break	break	no break	break	no break	break	no break
Bias	0.068	-0.001	0.154	0.019	0.226	0.030	0.305	0.049
MSE	0.054	0.027	0.087	0.026	0.162	0.041	0.299	0.062
RMSE	0.232	0.165	0.295	0.160	0.402	0.203	0.547	0.248
SE	0.221	0.165	0.252	0.159	0.332	0.201	0.454	0.243
MAE	0.152	0.118	0.214	0.135	0.299	0.165	0.372	0.215
MAPE	0.015	0.012	0.021	0.013	0.029	0.016	0.036	0.021

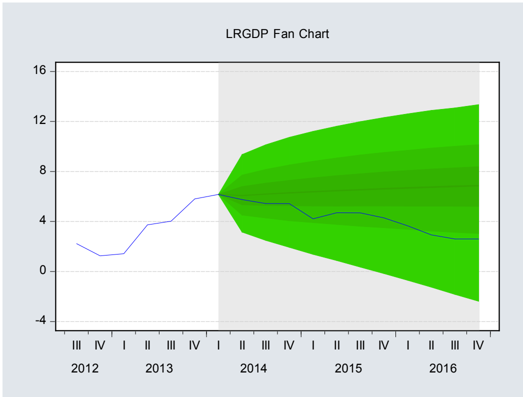
As can be seen in Figure 2, the lighter region corresponds to 90%, 60% and 30% confidence intervals. The line in the middle denotes the mode. The charts are appraised based on the confidence interval within which the forecasted series fall. While forecasted LINF and LMSS fall within the 30% confidence bound indicating the reliability of the model's prediction power, LRGDP and LTRA fall within the 60% bound, with the latter exceeding this bound after 2016Q2 indicating the slowdown in economic activity. Likewise, LASI exhibits a similar pattern but falls marginally outside the 90% confidence band, reflecting recessionary pressure and short-term capital reversal. However, the forecast of exchange rate after 2014Q4 exceeds the 90% confidence bounds and maintains an upward trend thereafter. This may be traced to the depreciation of the naira exchange rate as a result of negative crude oil price shocks that constrained foreign exchange supply.

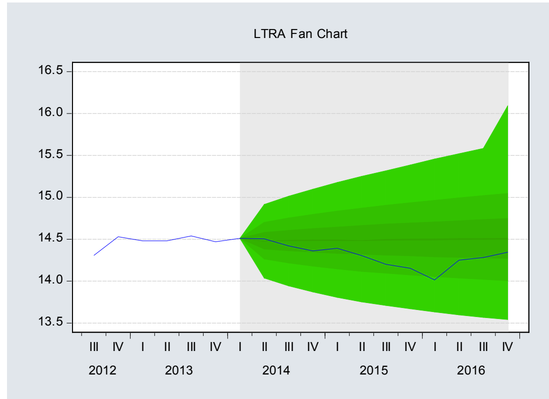
Table 7: Rolling Window Forecast Approach (LASI)

	Horizon 1		Horizon 2		Horizon 3		Horizon 4	
	break	no break	break	no break	break	no break	break	no break
Bias	0.090	-0.011	0.172	0.001	0.230	0.005	0.289	0.020
MSE	0.061	0.029	0.091	0.031	0.148	0.050	0.240	0.072
RMSE	0.246	0.169	0.302	0.175	0.385	0.225	0.490	0.268
SE	0.229	0.169	0.248	0.175	0.308	0.225	0.395	0.267
MAE	0.173	0.128	0.230	0.148	0.305	0.193	0.364	0.238
MAPE	0.017	0.013	0.022	0.014	0.030	0.019	0.035	0.023

Figure 4: Fan Charts of Variables







5. SUMMARY AND CONCLUSION

This paper forecasts the behaviour of selected macroeconomic variables in Nigeria with emphasis on RGDP and all-share index. This issue has generated substantial concern in view of its implications for macroeconomic and market stability. The empirical analysis was based on data between 1999Q1 and 2016Q2. The findings reveal that the model predicted macroeconomic fundamentals quite well even though the VECM performed better than the ARIMA model. This was validated by the forecast evaluation statistics. The result also shows that exchange rate pass-through to inflation was significant in the build-up to the 2016 recession and perhaps policy response lags may have accounted for the slow recovery. The all-share index fluctuated with a downward trend due to induced demand- and supply-side shocks. This was driven by short-term capital reversal as well as upward pressure on the naira exchange rate and its volatility. The outcome of the VECM forecast was reinforced by the ARIMA-based expanding and rolling window forecasting techniques. The persistent depreciation of the naira exchange rate and lagged response of output to changes in monetary policy in addition to a contemporaneous capital reversal from the Nigerian stock market affected other variables. Therefore, macroeconomic stability remains crucial to minimising contemporaneous capital reversals and restoring market confidence. In sum, efforts should be geared towards harmonising macroeconomic policy design and implementation.

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APPENDICES

Appendix 1: Summary statistics

	ASI	EXR	INF	MSS	RGDP	TRB
Mean	25321.99	161.43	94.87	8278193.00	7686691.00	234461.70
Maximum	63016.56	490.00	217.89	23076471.00	28398205.00	699825.40
Minimum	4890.80	94.00	29.48	609030.10	1087.91	-287481.40
Std. Dev.	13191.83	68.41	51.63	6817914.00	10047836.00	222746.00
Skewness	0.64	3.26	0.57	0.50	0.66	0.01
Kurtosis	3.28	14.46	2.24	1.93	1.69	2.49
Jarque-Bera	5.10*	521.56*	5.54*	6.44*	10.41*	0.77
Observations	72.00	72.00	72.00	72.00	72.00	72.00

Note: * indicates 5% significance.

Appendix 2: Correlation Matrix

	ASI	EXR	INF	MSS	RGDP	TRB
ASI	1.0000	0.1392	0.4818	0.4620	0.2832	0.2934
EXR	0.1392	1.0000	0.7589	0.7254	0.6779	-0.3582
INF	0.4818	0.7589	1.0000	0.9898	0.9314	-0.0911
MSS	0.4620	0.7254	0.9898	1.0000	0.9316	-0.0931
RGDP	0.2832	0.6779	0.9314	0.9316	1.0000	-0.1332
TRB	0.2934	-0.3582	-0.0911	-0.0931	-0.1332	1.0000

Appendix 3: Stationarity Test

	ADF		PP	
Variables	Level	First Diff	Level	First Diff
LASI	-0.384	-8.736*	-0.384	-8.736*
LEXR	-0.973	-8.834*	-1.016	-8.836*
LINF	-0.905	-8.824*	-0.939	-8.824*
LMSS	-0.587	-8.805*	-0.609	-8.805*
LRGDP	-0.646	-8.384*	-0.646	-8.384*
LTRA	-0.471	-8.841*	-0.471	-8.841*

Note: * implies significance at 5%.

Appendix 4: Cointegration Test

No. of CE(s)	Eigen	Trace	Critical Val.	P-Val.
None *	0.492	132.841	95.754	0.000
At most 1 *	0.443	87.432	69.819	0.001
At most 2 *	0.288	48.196	47.856	0.046
At most 3	0.230	25.466	29.797	0.146
At most 4	0.110	7.965	15.495	0.469
At most 5	0.003	0.190	3.841	0.663